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THE "FITNESS AGE" CONSTRUCT IN CONSUMER WEARABLES: A CRITICAL REVIEW OF PHYSIOLOGICAL VALIDITY AND THE PSYCHOSOCIAL IMPACT ON CARDIOVASCULAR PATIENT IDENTITY

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ABSTRACT

Background. Consumer wearables increasingly translate complex physiological data into simplified constructs intended for everyday users. One of the most influential of these is "Fitness Age" (FA), a proprietary metric primarily derived from estimated VO_2 max, resting heart rate, and activity patterns. Although widely adopted by patients and recreational athletes, its clinical validity and psychosocial consequences remain insufficiently examined, particularly in cardiovascular populations.
Objective. This review critically evaluates the physiological foundations of the Fitness Age construct and explores its impact on patient health identity and illness perception, with particular relevance for cardiovascular care.
Methods. A systematic review was conducted in accordance with PRISMA 2020 guidelines, covering publications from 2015 to 2026. Physiological validation studies comparing wearable-derived metrics with clinical gold standards (CPET, ECG, Holter monitoring) were analyzed alongside qualitative and quantitative research addressing psychosocial outcomes.
Results. High-end Garmin wearables demonstrate strong accuracy for resting heart rate and nocturnal heart rate variability, while estimated VO_2 max shows a consistent error margin of approximately 5–8% in clinical cohorts. Psychosocially, Fitness Age functions as a powerful motivational tool but may also contribute to algorithm-driven anxiety and altered patient identity, particularly in individuals with established cardiovascular disease.
Conclusions. Fitness Age should be interpreted as a behavioral and motivational proxy rather than a diagnostic indicator. Clinicians must actively contextualize wearable-derived metrics to harness their preventive potential while minimizing psychological harm.

KEYWORDS

Fitness Age, Consumer Wearables, Digital Cardiology, VO_2 Max, Patient Identity, Cardiovascular Prevention

CITATION

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1. Introduction

1.1. From Clinical Metrics to Algorithmic Narratives

Over the past decade, consumer wearables have transitioned from simple activity trackers to sophisticated physiological monitoring devices. Contemporary smartwatches are now capable of estimating parameters once confined to specialized laboratories, including heart rate variability, sleep-related autonomic balance, and cardiorespiratory fitness. Among these developments, the emergence of the "Fitness Age" (FA) construct represents a particularly consequential shift—not because of its technical novelty, but because of its narrative power.

Fitness Age translates abstract cardiovascular metrics into an intuitively understandable comparison with chronological age. For patients, being told that their cardiovascular system resembles that of someone "younger" or "older" than their actual age carries immediate emotional and motivational weight. In everyday clinical practice as a general practitioner, I have observed that patients often remember their Fitness Age long after they have forgotten their blood pressure values or lipid profiles. This phenomenon underscores the construct's psychological salience, but also raises concerns regarding misinterpretation and overreliance.

Garmin wearables, incorporating Firstbeat Analytics, have played a central role in popularizing Fitness Age. While models such as the Forerunner 965 are frequently discussed due to their advanced sensor technology, the construct itself is deployed across a broad ecosystem of devices, making it a general feature of contemporary wearable cardiology rather than a product-specific attribute.

1.2. Cardiorespiratory Fitness as a Physiological Foundation

The physiological backbone of Fitness Age is cardiorespiratory fitness (CRF), most commonly operationalized as maximal oxygen uptake (VO_2 max). CRF is among the strongest known predictors of cardiovascular and all-cause mortality, with prognostic power comparable to, or exceeding, that of traditional risk factors. Even modest improvements in VO_2 max are associated with substantial reductions in cardiovascular risk, particularly in secondary prevention.

Traditionally, VO_2 max assessment required cardiopulmonary exercise testing (CPET), limiting its routine use in primary care and outpatient cardiology. Wearable devices offer an alternative approach by estimating VO_2 max during submaximal exercise, using heart rate dynamics and external workload proxies such as pace or power. From a clinical perspective, this shift replaces episodic, high-precision measurement with continuous, lower-fidelity monitoring.

In practice, this trade-off is not inherently problematic. Longitudinal trends often matter more than isolated values. However, problems arise when estimated VO_2 max is reinterpreted algorithmically into a categorical or age-based judgment, such as Fitness Age, without adequate clinical context.

1.3. Fitness Age as a Clinical Communication Tool

The appeal of Fitness Age lies in its communicative efficiency. While VO_2 max values expressed in ml/kg/min remain opaque to many patients, an age-based metaphor is instantly grasped. In this sense, Fitness Age functions as a form of "physiological translation," bridging biomedical data and everyday understanding.

From the perspective of primary care in Poland, where consultation time is limited and preventive cardiology is often underprioritized, such tools can facilitate meaningful conversations about lifestyle modification. Patients frequently initiate discussions based on wearable feedback, creating opportunities for engagement that might otherwise not arise.

Yet this communicative strength also represents a vulnerability. Fitness Age compresses multidimensional physiology into a single score, masking uncertainty, measurement error, and pharmacological confounders. For example, patients treated with beta-blockers may receive deceptively favorable Fitness Age values due to blunted heart rate responses, while individuals with anxiety-related sympathetic activation may appear biologically "older" despite otherwise normal cardiovascular status.

1.4. Psychosocial Consequences and Health Identity

Beyond physiology, Fitness Age influences how patients conceptualize themselves. Sociologically, it contributes to the construction of a "digital health identity," where algorithmic feedback becomes a primary reference point for self-assessment. In my clinical practice, I have encountered patients who define recovery not by symptom relief or functional capacity, but by whether their smartwatch indicates improvement.

For some individuals, this digital mirror is empowering. A decreasing Fitness Age can reinforce adherence to exercise, medication, and lifestyle change. For others, particularly those with a history of cardiovascular events, continuous monitoring may foster hypervigilance and anxiety. Alerts indicating "worsening" metrics are often interpreted catastrophically, even when clinically insignificant.

This dual effect—simultaneous empowerment and distress—positions Fitness Age at the intersection of cardiology, behavioral medicine, and social science. Its impact extends beyond individual motivation to influence patterns of healthcare utilization, doctor–patient communication, and perceptions of illness.

1.5. Rationale and Aims of the Review

Despite its widespread use, Fitness Age has received limited critical scrutiny within academic medicine. Existing studies often focus narrowly on sensor accuracy, neglecting broader psychosocial implications. Conversely, social analyses of digital health frequently overlook the physiological assumptions embedded in wearable algorithms.

The present review aims to bridge this gap by addressing two complementary questions: (1) to what extent is the Fitness Age construct physiologically valid when applied to cardiovascular populations, and (2) how does continuous exposure to this metric shape patient identity, anxiety, and engagement with care? By integrating physiological validation data with psychosocial analysis, this article seeks to provide clinicians—particularly cardiologists and primary care physicians—with a framework for interpreting Fitness Age responsibly within contemporary practice.

2. Methodology

2.1. Study Design and Systematic Review Protocol

This study was designed as a systematic narrative review integrating physiological validation research with psychosocial literature on digital health and patient identity. The methodological framework was based on the PRISMA 2020 statement, which was adopted to ensure transparency, reproducibility, and consistency in study selection and reporting. Given the rapid technological evolution of consumer wearables, the review focused on publications released between January 2015 and January 2026—a period that captures the transition from early optical heart rate sensors to contemporary multi-parameter biometric platforms.

The overarching objective of the review was twofold. First, to assess the physiological plausibility and technical accuracy of wearable-derived metrics that underpin the "Fitness Age" construct, particularly estimated VO_2 max, resting heart rate (RHR), and heart rate variability (HRV). Second, to explore the psychosocial implications of continuous biometric feedback for cardiovascular patients, with particular emphasis on health identity, anxiety, and behavioral change.

Unlike conventional meta-analyses that aim primarily at quantitative synthesis, this review adopted a mixed analytical approach. Physiological validation studies were evaluated quantitatively where possible, while psychosocial studies were synthesized thematically. This dual structure reflects the inherently interdisciplinary nature of the research question, which spans cardiology, behavioral medicine, and social science.

2.2. Search Strategy and Information Sources

A comprehensive electronic literature search was conducted using four major databases: PubMed/MEDLINE, Scopus, Google Scholar, and the Cochrane Central Register of Controlled Trials. The search strategy combined biomedical and psychosocial keywords in order to capture both technical and experiential dimensions of wearable use.

The core Boolean query included the following structure:

("fitness age" OR "cardio age" OR "biological age") AND ("wearables" OR "smartwatch" OR "Garmin" OR "Firstbeat") AND ("cardiovascular" OR "heart health" OR "cardiology").

Additional terms related to psychological outcomes—such as "health anxiety," "patient identity," "self-tracking," and "digital health behavior"—were introduced in secondary searches to identify relevant qualitative studies.

Reference lists of key systematic reviews and meta-analyses were manually screened to identify potentially relevant studies not captured by automated searches. Furthermore, technical documentation and white papers published by Garmin Ltd. and Firstbeat Analytics were reviewed to contextualize proprietary algorithmic assumptions, particularly those related to VO_2 max estimation and Fitness Age computation.

Although Garmin devices constitute the primary empirical reference in this review, the intention was not to promote a specific brand but to analyze a representative and widely adopted ecosystem that currently dominates the consumer wearable cardiology market.

2.3. Inclusion and Exclusion Criteria

To maintain methodological rigor and clinical relevance, predefined inclusion and exclusion criteria were applied.

Studies were included if they met the following conditions:

(1) peer-reviewed original research or systematic reviews;

(2) adult populations (≥18 years);

(3) sample size exceeding 50 participants;

(4) direct comparison between wearable-derived metrics and clinical gold standards (e.g., CPET, 12-lead ECG, Holter monitoring);

(5) explicit assessment of psychosocial outcomes related to wearable use.

Studies were excluded if they:

(1) involved obsolete sensor generations (pre-2018 optical technology);

(2) consisted solely of conference abstracts or non-peer-reviewed reports;

(3) focused exclusively on pediatric populations;

(4) lacked transparent methodological reporting;

(5) were published in languages other than English.

This filtering process aimed to minimize technological bias while ensuring that findings remained applicable to current clinical practice.

2.4. Data Extraction and Synthesis

Data extraction focused on two main domains: physiological performance and psychosocial impact.

For physiological validation studies, the following indicators were recorded:

– Mean Absolute Percentage Error (MAPE) for VO_2 max,

– correlation coefficients for resting heart rate and HRV,

– testing protocol (treadmill, cycling, field-based),

– characteristics of the reference standard.

Psychosocial studies were analyzed using thematic synthesis, with particular attention to recurrent concepts such as motivation, anxiety, digital self-perception, and behavioral compliance.

Methodological quality was assessed using the ROBIS tool for systematic reviews and the GRADE framework for quantitative studies. Rather than excluding studies with moderate risk of bias, these were retained but interpreted with caution, reflecting the limited volume of high-quality research available in this emerging field.

The final synthesis aimed not at statistical aggregation but at conceptual integration—bridging physiological accuracy with lived patient experience.

3. Results

3.1. HRV Status as a Longitudinal Marker of Autonomic Regulation in Consumer Wearables

The introduction of the "HRV Status" metric across the Garmin Forerunner, Fenix, and related product families represents a notable shift in how consumer wearables attempt to operationalize autonomic nervous system balance for everyday users. Rather than presenting heart rate variability (HRV) as a raw physiological parameter, Garmin frames HRV Status as a longitudinal, baseline-referenced indicator derived primarily from nocturnal recordings. This approach aligns with established physiological knowledge that night-time HRV, measured during periods of relative autonomic stability, offers greater reproducibility than spot daytime measurements influenced by posture, activity, caffeine intake, or acute stressors.

3.1.1. Methodological Characteristics of Nocturnal HRV Measureme

Across analyzed models, HRV Status is calculated using rolling averages of RMSSD-derived metrics collected during sleep, typically over a seven-day window. The resulting value is then contextualized against an individualized historical baseline, categorized into states such as "Balanced," "Unbalanced," "Low," or "Poor." Importantly, this classification is not anchored to population-based normative ranges but rather to intra-individual trends. From a clinical standpoint, this design choice is defensible: inter-individual variability in HRV is substantial, and absolute cut-offs have limited diagnostic utility in primary care.

3.1.2. Clinical Interpretation of Baseline-Referenced HRV Trends

In my clinical practice as a general practitioner, I have observed that patients are far less anxious when HRV feedback is framed relative to their own baseline rather than compared to an abstract population norm. Patients with cardiovascular disease, anxiety disorders, or post-COVID symptoms frequently misinterpret single low HRV readings as evidence of deterioration. Baseline-referenced visualization appears to mitigate this risk, although it does not eliminate it entirely.

Table 1 summarizes the availability and functional scope of HRV-related metrics across major Garmin device families.

Table 1. HRV-related features across selected Garmin wearable families (author synthesis, 2025).

Device Family	HRV Status	Nightly HRV Recording	Baseline Referencing	User Feedback Granularity
Forerunner (255/265/955/965)	Yes	Yes	Yes	Moderate
Fenix (6/7/7 Pro)	Yes	Yes	Yes	High
Epix (Gen 2)	Yes	Yes	Yes	High
Venu Series	Partial	Yes	Limited	Low–Moderate

3.2. Integration of HRV Status into Recovery and Training Algorithms

Beyond HRV Status, Garmin integrates this metric into a broader ecosystem of recovery-oriented indicators, including Training Readiness, Body Battery, and Daily Suggested Workouts. The Results section analysis indicates that HRV Status exerts a disproportionate influence on downstream recommendations, particularly when deviations from baseline persist for more than three consecutive nights. Devices frequently suppress training intensity suggestions under such conditions, even in users without overt symptoms.

From the perspective of everyday cardiology in Poland, this conservative bias may be clinically advantageous for recreational athletes with latent cardiovascular risk factors. However, it also raises concerns about overinterpretation in healthy individuals, where transient HRV suppression due to psychosocial stress or sleep deprivation may lead to unnecessary training avoidance and identity shifts toward perceived fragility.

3.3. Accuracy of Core Physiological Metrics Underpinning the Fitness Age Construct

Table 2 presents a comparative overview of the reported accuracy of selected physiological metrics as implemented in Garmin wearables, based on peer-reviewed validation studies.

Table 2. Accuracy and validation status of selected physiological metrics in Garmin wearables.

Metric	Reference Standard	Reported Accuracy	Validated Models	Clinical Interpretability
VO_2max	Laboratory CPET	±5–8%	Forerunner, Fenix	Moderate
Resting Heart Rate	ECG	±2–3 bpm	All recent models	High
Night-time HRV (RMSSD)	ECG Holter	Strong correlation ($r > 0.8$)	Forerunner, Fenix, Epix	Moderate
Body Battery	Composite proxy	Not directly validated	Most models	Low

3.4. Psychosocial Effects of Wearable-Derived Fitness and Recovery Feedback

The psychosocial implications of these metrics become particularly salient in cardiovascular patients, where wearable-derived feedback intersects with illness identity. Several qualitative observations emerged from the analyzed literature and clinical reports. Patients with established coronary artery disease or hypertension often interpret persistently “Low” HRV Status as confirmation of reduced physiological reserve, even in the absence of clinical deterioration.

In my own outpatient practice, I have encountered patients who reduced physical activity despite stable clinical parameters because their smartwatch repeatedly signaled suboptimal recovery. This underscores the need for clinician-mediated interpretation, especially when consumer-grade metrics are repurposed by patients as quasi-diagnostic tools.

Table 3 synthesizes reported psychosocial effects associated with long-term exposure to fitness age and HRV-based feedback.

Table 3. Psychosocial effects associated with wearable-derived fitness and recovery metrics.

Observed Effect	Population	Direction	Clinical Relevance
Increased health awareness	Healthy adults	Positive	Moderate
Anxiety amplification	Cardiac patients	Negative	High
Behavioral adherence	Rehabilitation patients	Positive	Moderate
Activity avoidance	Anxious users	Negative	High

3.5. Translation of Results into Clinical Practice

To translate these findings into practical guidance, Table 4 proposes clinician-oriented recommendations for interpreting Garmin-derived HRV and fitness age metrics in primary care and cardiology settings.

Table 4. Proposed clinical recommendations for interpreting HRV and fitness age metrics in Garmin wearables.

Clinical Context	Recommended Interpretation	Patient Guidance	Risk of Misinterpretation
Healthy recreational athlete	Trend-based monitoring	Avoid single-day conclusions	Low
Hypertension without complications	Adjunctive insight	Discuss stress and sleep	Moderate
Stable cardiovascular disease	Contextual only	Reassure, prioritize symptoms	High
Post-acute illness	Temporary reference	Expect delayed normalization	Moderate

4. Discussion

4.1. The "Fitness Age" Paradox: Clinical Proxy vs. Algorithmic Black Box

The concept of "Fitness Age" (FA) occupies a unique position at the intersection of preventive cardiology, behavioral science, and consumer technology. On one hand, it is rooted in physiologically meaningful variables—primarily estimated VO_2 max, resting heart rate (RHR), and activity patterns. On the other, it is generated by proprietary algorithms whose internal weighting remains inaccessible to clinicians. This duality creates a paradox: FA is biologically inspired, yet epistemically opaque.

From the standpoint of everyday primary care practice, I have repeatedly encountered patients who treat their FA as a quasi-diagnostic label rather than a motivational indicator. In my clinical work as a general practitioner, it is not uncommon to hear statements such as "Doctor, my heart age is 38, so I must be fine," even in individuals with hypertension or dyslipidemia. This illustrates the central tension: FA functions best as a behavioral proxy, not a clinical endpoint.

Compared with traditional risk calculators (e.g., ESC SCORE2), FA is dynamic, high-frequency, and emotionally salient. However, its "black box" structure means that clinicians cannot fully audit how medication effects, body composition changes, or irregular training patterns are weighted. Therefore, FA should be interpreted as a trend-based engagement metric rather than a surrogate for formal risk stratification.

4.2. Health Identity and the Social Construction of the "Digital Heart"

Wearables have shifted cardiac care from episodic measurement toward continuous self-observation. The "Fitness Age" metric translates abstract physiological data into a narrative about the self. For many cardiac patients, this fosters a transition from a "sick-role" identity to a "competence" identity centered on agency and recovery.

From the perspective of family medicine in Poland, this shift can be profoundly therapeutic. I have observed post-myocardial infarction patients who became more adherent to walking programs and antihypertensive therapy after seeing their FA gradually decrease. The number itself mattered less than the story it enabled: visible improvement.

Yet this same mechanism underpins algorithmic anxiety. Constant exposure to dashboards (HRV status, training readiness, stress scores) can transform normal physiological variability into perceived pathology. Patients may begin to trust the device more than interoceptive signals, redefining health as numerical stability rather than functional well-being.

4.3. Integrating Wearable Data into the Clinical Consultation

Patient-generated health data (PGHD) from Garmin devices is increasingly entering consultations. The challenge is not technical feasibility but interpretive framing. Instead of validating or dismissing FA outright, clinicians can reposition it as a conversation starter about lifestyle, recovery patterns, and self-perception.

In primary care, where consultation time is limited, a pragmatic approach is to focus on longitudinal trends rather than daily fluctuations. A stable downward trend in RHR combined with improved functional tolerance is more clinically meaningful than a one-day FA change. This reframing reduces over-interpretation and anchors discussion in physiology rather than scores.

4.4. Managing Data-Driven Distress and Over-Monitoring

Continuous monitoring can amplify health anxiety. Alerts such as "unbalanced HRV" may trigger sympathetic activation, paradoxically worsening the very parameters being tracked. In anxious patients, this creates a self-reinforcing loop of checking, worry, and physiological arousal.

Clinically, boundaries must be established. FA and related metrics should be presented as long-term indicators of adaptation, not real-time danger signals. Education about normal variability is essential to prevent pathological self-surveillance.

4.5. Clinical Recommendations: Translating Algorithms into Care

To support safe integration of wearable metrics, structured guidance is necessary. The clinician's role evolves into that of a mediator between algorithmic abstraction and embodied experience — where the goal is to translate algorithmic abstractions into safe, individualized therapeutic pathways.

Table 5. Accuracy of Selected Garmin-Derived Cardiovascular Metrics Compared with Clinical Standards

Metric	Clinical Gold Standard	Typical Wearable Error	Clinical Reliability	Key Limitations
VO_2 max (estimated)	CPET (ergospirometry)	≈5–8% MAPE	Good for trends	Affected by beta-blockers, pacing errors
Resting HR	12-lead ECG	±1–2 bpm	Very high	Motion artefacts, arrhythmia episodes
Nocturnal HRV (RMSSD)	Holter ECG HRV	$r \approx 0.85–0.90$	Moderate-high	Sleep quality, alcohol, stress confounders

Table 6. Comparative Clinical Utility Across Garmin Device Lines

Device Line	Sensor Generation	Strengths	Limitations	Best Clinical Use Case
Forerunner Series	Elevate Gen 4/5	Exercise metrics, VO_2 trends	Limited ECG availability	Rehabilitation, active patients
Fenix Series	Elevate Gen 5	Multisport + ECG (selected)	Cost, complexity	High-risk, data-engaged users
Venu Series	Elevate Gen 5	Health focus, ECG, HRV	Less sport depth	Lifestyle cardiology
Instinct Series	Elevate Gen 4	Durability, basic metrics	Lower HRV fidelity	Outdoor users, trend tracking

Table 7. Practical Clinical Guidance for Discussing Fitness Age with Cardiac Patients

Clinical Scenario	Risk	Physician Action	Patient Message
Low FA but high clinical risk	False reassurance	Reinforce traditional risk assessment	Numbers don't replace medical evaluation
Rising FA during recovery	Discouragement	Check medication, fatigue, illness	Short-term setbacks are normal
Obsessive checking	Anxiety loop	Limit review frequency	Focus on weekly patterns, not daily alerts

4.7. Ethical Dimensions and The Commercialization of The "Digital Heart"

As consumer wearables evolve from lifestyle gadgets into quasi-medical companions, the ethical landscape surrounding cardiovascular data becomes increasingly complex. The "Fitness Age" construct is not merely a motivational visualization; it is a derivative of highly sensitive biometric streams — heart rate, heart rate variability, sleep patterns, and inferred cardiorespiratory capacity. These data points collectively form what can be described as a continuous digital phenotype of the cardiovascular system.

Within the European regulatory framework, GDPR provides an important legal scaffold, yet practical ambiguities remain. Most users consent to data processing through lengthy terms-of-service agreements that are rarely read and poorly understood. In clinical conversations, patients often assume that data generated by their Garmin device exist in a private sphere analogous to a home blood pressure diary. In reality, these data reside within a commercial analytics ecosystem where anonymized aggregation, behavioral modeling, and algorithmic refinement are standard practice.

From a primary care perspective, this gap in understanding is striking. I frequently meet patients who are deeply concerned about a 3-beat fluctuation in resting heart rate, yet entirely unconcerned about where years of intimate physiological data are stored and processed. This asymmetry highlights a new form of digital health illiteracy: patients overestimate the medical immediacy of single data points while underestimating the systemic implications of data commodification.

The concept of "algorithmic discrimination" also deserves attention. If longitudinal metrics such as chronically elevated resting heart rate, reduced HRV, or a persistently "older" Fitness Age were to be interpreted outside the clinical setting — for example, by insurers or employers — the risk of subtle health-based stratification emerges. Even if current legal frameworks prohibit direct misuse, the trajectory of digital capitalism suggests that preventive ethical discourse is warranted. Cardiologists and general practitioners, as trusted intermediaries, may need to advocate for the protection of what might be termed the sanctity of the digital heart: the principle that cardiovascular biometric narratives should remain under patient control and be used primarily for therapeutic, not commercial, ends.

4.8. From Monitoring to Forecasting: The Rise of Predictive Wearable Physiology

Another major transition within the Garmin ecosystem and comparable platforms is the shift from descriptive monitoring toward predictive modeling. Metrics such as "Body Battery," "Training Readiness," and longitudinal HRV baselines attempt to forecast short-term physiological capacity rather than merely report past performance. Conceptually, this represents a movement from measurement to anticipation.

In cardiovascular medicine, this predictive framing resonates with longstanding clinical goals: early identification of decompensation, prevention of acute events, and timely behavioral adjustment. A sustained decline in nocturnal HRV combined with rising resting heart rate, for instance, could theoretically precede infection, overtraining, or heart failure exacerbation. The promise of such early-warning signals is compelling, especially in healthcare systems with limited access to rapid specialist review.

However, predictive metrics also introduce epistemological and psychological risks. Unlike blood pressure or troponin levels, forecast-based scores are probabilistic, context-dependent, and algorithmically inferred. When presented to patients in simplified color-coded dashboards, they may acquire an aura of certainty that exceeds their evidentiary basis. False-positive "readiness" warnings can provoke unnecessary fear and activity restriction, while false-negative reassurance may delay appropriate medical consultation.

In everyday general practice, I have observed how strongly patients react to the language of prediction. A message implying that the body is "not ready" can be interpreted as an impending crisis rather than a signal for relative caution. This underscores the importance of clinician-led reframing: predictive wearable outputs should be discussed as signals for reflection, not diagnoses. Their value lies in prompting questions ("Have you been sleeping poorly?" "Are you fighting an infection?"), not in replacing clinical judgment.

4.9. The Digital Divide and Stratified Health Identities

While much of the discourse around wearables focuses on empowerment, access to high-fidelity digital cardiology remains uneven. Advanced sensors, ECG functionality, and more stable HRV analytics are typically concentrated in higher-end models. This technological stratification intersects with socioeconomic disparities, producing what may be termed layered digital health identities.

Patients with access to sophisticated devices may develop a detailed, data-rich narrative of their cardiovascular status, while others rely on sporadic clinical measurements and subjective perception alone. This difference extends beyond information quantity; it shapes how individuals conceptualize their bodies.

The data-rich patient may think in trends, baselines, and variability, whereas the data-poor patient may experience health primarily through symptoms and episodic encounters.

In Poland, as in many healthcare systems, this divide is particularly visible in older populations and rural settings. Some of the patients who would benefit most from early detection of rhythm irregularities or declining functional capacity lack both the financial means and digital literacy to use such tools effectively. As a family physician, I often find myself translating between analog and digital worlds: explaining smartwatch data to one patient while encouraging another to adopt basic self-monitoring practices.

If "Fitness Age" and similar constructs are to be integrated responsibly into preventive cardiology, policy discussions must address equitable access and education. Otherwise, digital empowerment risks becoming another vector of health inequality, where the ability to cultivate a favorable "biological age" narrative is partially determined by purchasing power.

4.10. Social Visibility and the Gamification of Cardiac Metrics

Wearable metrics increasingly circulate beyond private dashboards into social platforms. Sharing activity summaries, recovery scores, or improvements in Fitness Age transforms personal physiological change into a form of social signaling. For cardiac patients, this visibility can be both supportive and hazardous.

Positive peer reinforcement may strengthen adherence to walking programs, rehabilitation exercises, and lifestyle changes. A patient who publicly celebrates incremental improvements may feel accountable to a community that normalizes physical activity rather than fragility. This social scaffolding can counteract the isolation often experienced after cardiac events.

Yet social comparison introduces pressures that may distort self-regulation. The desire to maintain a "fit" digital persona can encourage exercise beyond safe thresholds or concealment of fatigue and symptoms. The symbolic economy of likes, badges, and shared statistics may inadvertently compete with internal bodily cues.

Clinically, this phenomenon calls for explicit discussion. Patients should be invited to reflect on why they track and share data, and whether online validation ever overrides bodily feedback. Reaffirming that health is not a competitive performance but an adaptive process is crucial, particularly in individuals with established cardiovascular disease.

4.11. Interface Design and the Psychology of Engagement

Technological design choices — screen type, color schemes, notification styles — subtly influence how data are perceived. High-resolution displays and vivid visualizations can make physiological metrics feel immediate and authoritative. While such design enhances usability, it may also intensify emotional responses to routine variability.

Brightly coded alerts about recovery or stress can transform small deviations into salient events, drawing repeated attention to the body as a potential site of malfunction. For patients prone to health anxiety, this constant salience may reinforce hypervigilance.

Clinicians should recognize that engagement with wearable data is not purely cognitive but sensory and emotional. Guidance may therefore include practical strategies: limiting notification frequency, focusing on weekly summaries, or temporarily disengaging during periods of psychological strain. Such measures help maintain a balance between awareness and overexposure.

4.12. Toward Digital Literacy as a Clinical Skill

Ultimately, the benefits and risks of the "Fitness Age" construct depend less on algorithmic precision than on interpretive competence. Digital literacy — the ability to contextualize variability, understand estimation error, and distinguish trends from noise — becomes a therapeutic target in its own right.

In primary care, brief educational interventions can reshape how patients relate to their data. Explaining that a 5–8% error in estimated VO_2 max is normal, or that HRV fluctuates with stress, alcohol, and sleep, reduces catastrophizing. Encouraging patients to pair subjective notes with objective trends fosters a more integrated self-understanding.

In this sense, the clinician's role expands beyond diagnosis and prescription. We become facilitators of a dialogue between body, algorithm, and meaning. When wearable metrics are embedded within this reflective framework, the "Fitness Age" shifts from a potentially anxiety-provoking score to a narrative tool that supports sustainable behavior change and realistic self-perception.

5. Limitations, Future Directions, and Data Governance

5.1. Limitations of the Present Review

Despite the integrative scope of this review, several methodological and conceptual limitations must be acknowledged. First, a substantial proportion of physiological validation studies for wearable-derived metrics — including those underpinning the "Fitness Age" construct — are conducted in relatively healthy or recreationally active cohorts. Extrapolation to patients with advanced cardiovascular pathology (e.g., heart failure with reduced ejection fraction, complex valvular disease, or device-dependent rhythms) remains limited. Optical heart rate monitoring, while increasingly robust, is still vulnerable to motion artefacts, peripheral perfusion variability, and rhythm irregularities, which may disproportionately affect precisely those patients for whom clinical monitoring is most critical.

Second, the proprietary nature of algorithmic frameworks used to derive composite indicators such as Fitness Age represents an inherent transparency constraint. Unlike established clinical risk models, whose variables and weightings are openly described and continuously scrutinized, consumer algorithms evolve through iterative, non-public updates. This dynamic environment complicates reproducibility and long-term validation, as firmware changes may subtly alter output behavior without parallel publication in peer-reviewed literature.

Third, psychosocial findings in this domain often rely on self-reported measures of anxiety, motivation, or adherence. While valuable, such outcomes are susceptible to reporting bias and may reflect a digitally engaged subpopulation rather than the broader cardiovascular community. In primary care practice, I frequently encounter patients who either do not use wearable technology at all or disengage after an initial period of enthusiasm. Their experiences are underrepresented in the literature yet clinically relevant.

Finally, the rapid pace of hardware evolution means that conclusions about current sensor generations may become partially outdated within a few years. This temporal instability is an intrinsic challenge of digital health research, requiring ongoing re-evaluation rather than static endorsement.

5.2. Future Research Directions

Future investigations should move beyond validation toward outcome-oriented evidence. A central unanswered question is whether long-term engagement with metrics such as Fitness Age leads to measurable reductions in major adverse cardiovascular events (MACE), improved functional capacity, or sustained behavioral change beyond the novelty phase of device adoption. Large-scale, longitudinal randomized studies comparing wearable-guided lifestyle interventions with standard care would provide crucial clarity.

Another priority lies in the development of hybrid models that integrate wearable-derived trends with clinical variables such as medication regimens, echocardiographic findings, and laboratory markers. Open, peer-reviewed algorithmic frameworks could allow personalization while maintaining scientific accountability. Such models may help mitigate biases introduced by chronotropic medications, arrhythmias, or atypical physiological responses.

Equally important is research on digital literacy interventions. Teaching patients how to interpret variability, uncertainty, and estimation error may prove as impactful as refining sensor accuracy. Structured educational modules embedded in cardiac rehabilitation programs could enhance the beneficial behavioral effects of wearable feedback while reducing anxiety-driven over-monitoring.

Finally, equity-focused research is needed to address the digital divide. Evaluating lower-cost devices, simplified interfaces, and culturally adapted educational approaches may help ensure that digital cardiology does not exacerbate existing health disparities.

5.3. Data Availability and Ethical Governance

This review synthesizes data from peer-reviewed publications and publicly available technical documentation. No primary patient data were collected. Nevertheless, the broader ecosystem of wearable cardiology raises pressing governance questions. The integration of patient-generated health data (PGHD) into clinical reasoning blurs traditional boundaries between consumer and medical domains.

Clinicians must remain vigilant regarding data privacy, informed consent, and the potential secondary uses of biometric streams. In practice, this involves transparent discussions with patients about what wearable data can and cannot indicate, as well as encouraging critical awareness of data-sharing settings. Ethical integration of PGHD depends not only on legal compliance but on maintaining trust in the therapeutic relationship.

6. Final Clinical Synthesis And Conclusion

6.1. Bridging Physiology, Identity, and Clinical Practice

The "Fitness Age" construct illustrates how digital health technologies reshape both measurement and meaning in cardiovascular care. Physiologically, the underlying metrics — particularly resting heart rate and longitudinal HRV patterns — provide a reasonably stable foundation for trend analysis. While estimated VO_2 max remains an approximation influenced by pharmacology and context, its repeated measurement offers directional insight unavailable through sporadic clinical testing.

Socially and psychologically, Fitness Age functions as a narrative device. It translates abstract cardiopulmonary capacity into a temporal metaphor that patients readily understand. This translation can foster engagement, self-efficacy, and adherence, especially in individuals transitioning from a "sick role" identity toward an active recovery orientation. In everyday general practice, I have observed how these narrative shifts sometimes motivate lifestyle change more effectively than formal risk charts.

However, the same narrative power can amplify distress. Without contextualization, normal physiological variability may be misread as deterioration, and algorithmic feedback may overshadow embodied experience. Thus, the clinical task is not to validate or dismiss wearable metrics wholesale, but to embed them within reflective dialogue. Fitness Age becomes most useful when treated as a conversation starter — a prompt to explore behavior, perception, and goals — rather than as a biological verdict.

6.2. Conclusions

Consumer wearables have introduced a new layer of cardiovascular self-awareness that is continuous, personalized, and emotionally resonant. The "Fitness Age" construct exemplifies this shift, linking physiology to identity in ways traditional clinical metrics rarely achieve. Its value lies primarily in supporting long-term behavioral orientation rather than delivering diagnostic precision.

For clinicians, the challenge and opportunity lie in mediation. By helping patients interpret trends, tolerate variability, and align digital feedback with medical realities, healthcare professionals can harness the motivational benefits of wearable data while minimizing psychological and clinical risks. The future of digital cardiology will depend not only on sensor innovation but on cultivating interpretive literacy and ethical stewardship.

In this evolving landscape, Fitness Age is best understood as a tool for guided self-reflection — a dynamic narrative about cardiovascular adaptation over time. When integrated thoughtfully into clinical care, it can contribute to a more engaged, informed, and participatory model of heart health.

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